Image Processing for Crop Fields Segmentation on Satellite Data

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Abstract— **Crop yield estimation of agricultural fields is important at the national and regional scale. Remote Sensing (RS) data are attractive for land cover identification, classification and estimation, especially in the agricultural regions. Modeling the agricultural fields as spatial objects can be helpful to reflect the extensional uncertainties and therefore to characterize inaccuracy in parcel size estimation. The main goal of the project is to create maps of segmented agricultural fields using image processing techniques. As input data for crop segmentation algorithms the Satellite imagery is used from the Sentinel-2 satellite. These images include 13 spectral bands. For crop fields classification two statistical approaches are widely used in the literature: pixel-based and object-based. However, it is well known that classification procedures for homogeneous objects produce better results than per-pixel classification. However, there is a necessary preliminary step for object-based classification, which is segmentation. There exist three methods to deal with segmentation: edge-based, cluster-based and region-based. In this work we consider different approaches for image segmentation, apply them for satellite imagery of the agricultural fields and compare the obtained results. We evaluate the performance of the algorithms both visually and numerically.**

I. INTRODUCTION

The increasing public availability of satellite data sets makes possible the developing of different technologies for automatic classification for agriculture applications. However, it is very difficult to obtain satisfactory classification results using pixel-based approaches, in which each pixel is classified separately using only spectral information. Then, in the result of such classification due to abundant information of satellite imagery some artifacts can be produced, i.e. inconsistent salt-and-pepper classification map. To overcome these problems, object-oriented classification, which subdivides the image into meaningful homogeneous regions (i.e. crop fields) and classifies them on the basis of not only spectral properties but also shape, texture, and other topological features, has recently been proposed. One of the most important issues in object-oriented classification is the accurate segmentation of the input image because the quality of object-oriented classification is directly affected by the image segmentation quality.

Image segmentation plays a crucial role in various image processing applications in several domains, including medical and remote sensing. It describes the task of partitioning an image into several segments or regions. Before performing segmentation on images, sometimes image denoising must be done to remove the noises from the images and certain edge detectors like sobel, prewitt, roberts, canny are employed. After performing segmentation, the final resultant image is a cluster with similar features. Here, uses satellite images for performing segmentation. This paper shows the comparison of various segmentation techniques such as k-means, simple linear iterative clustering (SLIC) [8], threshold and Modified Seeded Region Growing (MSRG) segmentation algorithms in satellite images.

The segmentation techniques are classified as Detecting Similarities and Detecting Discontinuities. Detecting similarities is the process of dividing into regions based on some predefined aspects. It includes certain techniques such as K-means clustering method, Thresholding, Region Splitting and Merging etc. Detecting Discontinuities is the way of dividing image into partitions based on abrupt changes in the intensity [4].

In this work we have implemented the segmentation approaches, described in the section II, from scratch, as there are no existing standard libraries, especially for usage on multispectral data. Additionally, in the supporting Jupyter Notebooks we provide an evaluation pipeline for comparing different segmentation techniques both visually and numerically, which we reported in section III. To perform numerical comparison we wrote the code, which implements commonly used metrics for image segmentation evaluation that are also described in the section III. Sections IV and V are devoted to the results and discussion accordingly.

II. APPROACHES

Generally, segmentation algorithms can be broadly divided into edge-based, cluster-based and region-based algorithms. Edge-based algorithms detect object contours using the discontinuity property, whereas region-based algorithms focus on grouping pixels using the similarity property based on certain homogeneity criteria. The spatial domain of a processed image is used in both cases. Cluster-based segmentation algorithms use an iterative moving method that attempts to search for a cluster configuration to separate distinct structures in the spectral feature domain. The clustering technique does not consider spatial information. Edge-based segmentation has not been very successful because of its poor performance in the detection of textured objects. This approach also requires post-processing procedures, such as edge tracking or gap filling, to identify object contours.

A larger number of region-based segmentation algorithms has therefore been proposed for segmentation of remote sensing imagery. In this work we compare two such region-based algorithms for image segmentation, namely, Modified

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Seeded Region Growing (MSRG) Image Segmentation and Threshold Image Segmentation. Additionally, we have included one cluster-based algorithm, which uses K-Means technique, SLIC algorithm, based on superpixels and Split and Merge Segmentation method into our comparison.

A. MSRG Image Segmentation Algorithm

Conventional region growing is highly sensitive to the threshold value for stopping the growth of a region, and it produces different results depending on the selection of the scanning direction for seed points (i.e. as in [1]. Authors of [5] proposed a method for the segmentation of satellite imagery, which takes into account multiple-feature information, such as multispectral and edge information, and is more robust to the seed selection. In their approach, the Seeded Region Growing (SRG) algorithm [6] is modified to make use of information in all spectral bands and edge information for better image segmentation. A seed selection method based on the local variation characteristics of a multispectral edge is also developed to obtain seeds for the Modified SRG (MSRG) procedure.

The MSRG image segmentation algorithm consists of two stages. In the first stage, multispectral edge information is extracted using an entropy operator for the modified SRG procedure with preliminary smoothing. In the second stage, initial seed points are extracted through the proposed edge variation-based seed selection, which uses the obtained multispectral edge in a local region. Image segmentation is achieved by applying the MSRG procedure, which integrates the multispectral and gradient information to provide homogenous image regions with accurate and closed boundaries.

To generating edge image from multispectral image authors in [5] use an edge operator based on entropy, because it allows them to take into account edge information of all bands simultaneously, and not just to process only a single band. The entropy measure of individual bands, which provides information on the homogeneity of the window mask, is defined as follows

$$SH = \sum_{j=0}^{n} p_i \log p_i / \log(n+1) \tag{1}$$

where $p_i = a_i / \sum_{j=0}^{n} a_j$. SH is entropy measure of the central pixel in the local window, n is the total number of neighboring pixels, a_i represents the n pixel values, and p_i is the probability. The integrated entropy measures containing the contrast information of individual bands can be expressed as a linear combination of individual entropy measures:

$$H = \sum_{i=0}^{N} q_i SH_i, q_i = b_i / \sum_{i=0}^{N} b_i \tag{2}$$

N is the total number of bands, and b_i and SH_i indicate entropy measure of the individual bands respectively. The entropy of a multispectral image takes high values in edge regions and low values in flat regions.

Although, the entropy-based operator showed good results for generating edge image, we also tested the usual approaches based on ordinary edge-detection operators. We used operators described in [3], namely Sobel, Prewitt and Roberts.

To determine the seed points from the edge image, each central pixel moves toward the neighboring pixel having the lowest gradient, and this course is repeated until the point converges to the local minima and no more movement is made. The region having the same local minima shows a homogeneous property so that these local minima can be used by the seed points. However, according to various effects of image acquisition characteristics, a subtle difference of edge variation is presented even though these are extracted by the same region. If this property is not considered when the seed point is extracted, it extracts too many seed points and causes over-segmentation. Therefore, we extract the final seed points considering the difference of values between detected local minima and its neighboring eight pixels. If there are pixels for which the difference is within a tolerable range, the points are re-spread to other local minima. The final seed points are extracted through this process, and a tolerable range is determined by the edge difference between local minima and its neighboring pixel.

$$Tor(i) = \frac{\min(|G_i - G_k|)}{G_{\max} - G_{\min}}, k = 1, 2, ..., N \tag{3}$$

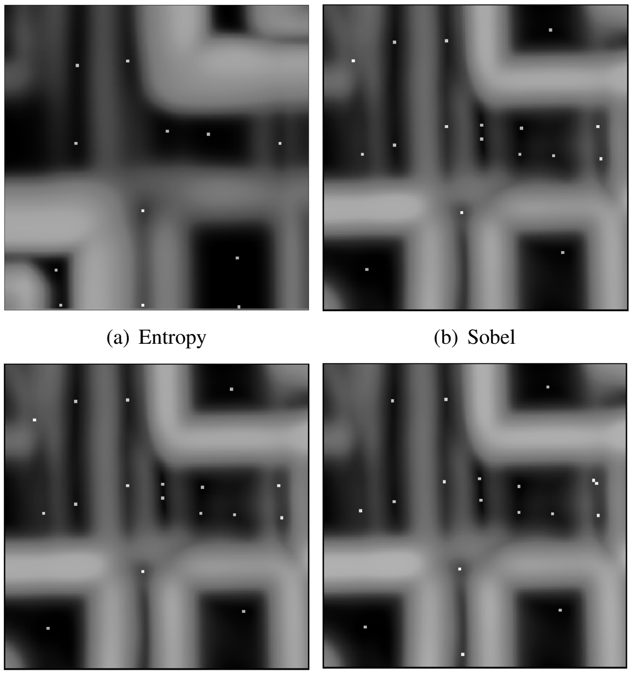
where G_i is the edge magnitude at a local minimum point i, N is the number of neighbours of G_i, G_k represents the N neighboring edge magnitudes, and $G_{\max}$ and $G_{\min}$ are the maximum and minimum magnitudes of the edge in the image, respectively. The local minima when the value of Tor is greater than a specified threshold is selected as seed points. Examples of the generated edge images with computed seed points (white dots) for different operators are shown on Fig. 1.

After that the actual Modified SRG comes. Given a set of seeds $S_1, S_2, , S_n$, each step of SRG involves adding one additional pixel to one of the seed sets. The pixels in the same regions are labelled with the same symbol and the pixels in different regions are labelled with different symbols. Let H be the set of all unallocated pixels that are adjacent to at least one of the labelled regions. In each step of the algorithm, one pixel is taken from set H and added to one of the regions with which neighbors $N(x, y)$ of the pixel intersect. The pixel is given the label of that region. All pixels of $N(x, y)$ are then examined and calculated the similarity to their neighboring regions. According to that similarity measure, we put them into set H in increasing order. The novel similarity measure that takes into account the edge strength difference as well as spectral difference is defined.

$$\phi(x, y) = \frac{I(x, y) \times \overline{I(x, y)}}{||I(x, y)||^2} |G(x, y) - \overline{G(x, y)}| \tag{4}$$

where

$$\overline{I(x, y)} = \frac{1}{m} \sum_{(x,y) \in R_i} I(x, y)$$



(a) Entropy (b) Sobel

(c) Prewitt (d) Roberts

Fig. 1. Edge Images with Seed Points for Different Operators

$$\overline{G(x,y)} = \frac{1}{m}\sum_{(x,y)\in R_i} G(x,y)$$

Where $I(x,y)$ indicates the pixel vector value of each component of the testing pixel (x,y), $\overline{I(x,y)}$ is the mean spectral vector for each region, $G(x,y)$ is the edge magnitude of the multispectral edge map, $\overline{G(x,y)}$ is the mean edge strength value for each region, R_i is the set of pixels included in each region, m is the number of pixels in each region, and $||.||$ and $\times$ represent the vector norm and inner product, respectively.

The SRG procedure is repeated until all pixels in the image have been allocated to regions. The implementation of SRG involves ordering the data of H as a linked list according to $\phi(x,y)$. However, authors in [5] apply heap-based Priority-Queue (PQ) data structure instead of the linked list because the time complexity of the priority queue is lower than that of the linked list. So, we are also using PQ in our code. An overview of the algorithm for implementing the proposed method is presented in Fig. 2.

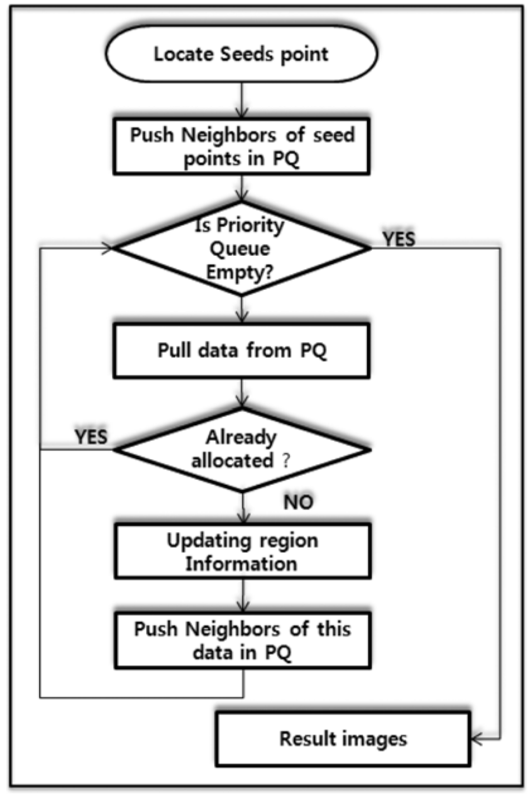


Fig. 2. The Algorithm Procedure of the MSRG

B. Threshold Image Segmentation Technique

This is the most basic, fundamental but powerful technique in segmentation. Always the color image or gray scale image is taken as input and binary image is produced as output. There are types of thresholding like local and global thresholding. If threshold is being set as constant called as global thresholding, otherwise it will be local thresholding [4]. In global case a color limit value is being set. It is being taken from the histogram of the image by looking onto the peaks formed. All the image pixels that lies greater than the threshold value, are set to white (1) and those lesser than the color limit are set to black (0).Thus, the resultant image consists of two regions (black and white). In this work we apply thresholding algorithm to individual channels of the satellite image. Setting local threshold allows to separate certain color range from the histogram of the processed image. Color is one of the feature of the specific crop field. So by choosing a specific color range from the smoothed image it is possible to distinguish similar crop fields. The following are the steps to be followed in doing thresholding technique.

1. Given a gray scale image.

2. Smooth the image in order to remove random high frequency components in the image.

3. Plot the histogram of the smoothed image. The graph should represent number of pixels that belong to certain color range.

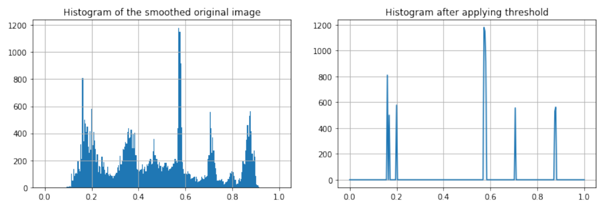
4. Define the minimum number of pixels that can compose one segmented region.

5. After applying this limit the main colors will remain in the new histogram, Fig.3.

6. Choose local color range for each main color in the resulting histogram. At this stage the original image is decomposed into several binary images representing certain color range.

7. Apply morphological transformations to obtained binary images, Fig.4

8. Combine individual regions to the final segmentation image.



(a) Histogram of the smoothed image

(b) Thresholded histogram

Fig. 3. Histogram comparison

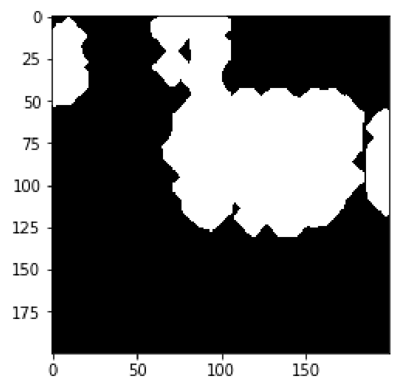


Fig. 4. Binary image of the certain region

It is also possible to apply color-based technique to color images, choosing specific RGB- or HSV- range. However, as we mentioned above, it is important to smooth the image before extraction of certain color regions. On the Fig. 5 there are a lot of noise that doesn't correspond to the color-labeled region. Original image is represented on the Fig. 7. Thresholding technique works a way better with smoothed images, see the result at Fig. 6. In order to obtain better results further erosions and dilatations can be applied to the binary image.

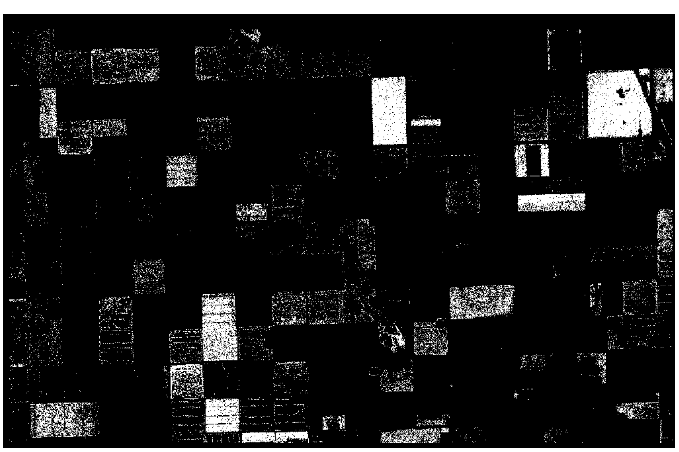


Fig. 5. Binary image of the specific HSV-range: $117 <= H <= 169$, $53 <= S <= 217$, $59 <= V <= 108$

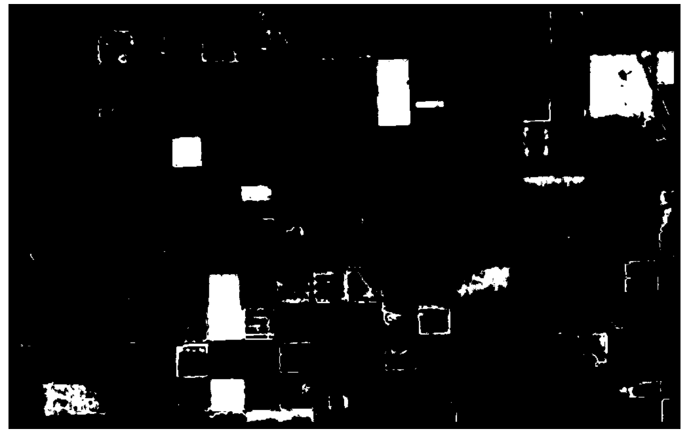


Fig. 6. Binary representation of the smoothed ($\sigma = 3$) image, HSV color range

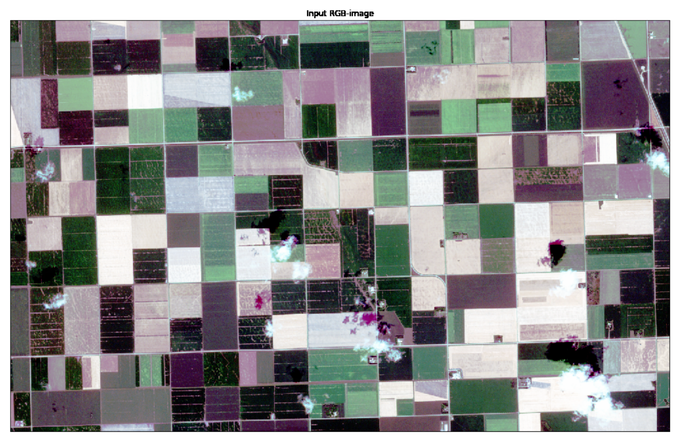


Fig. 7. Original 3-channel image

C. K-Means Cluster-Based Segmentation

In this work we also consider a simple cluster-based segmentation technique, which relies on K-Means clustering algorithm. In this method each pixels is represented by a feature vector consisting of spectral values of this pixel in different bands. Then, K-Means clustering is performed on this feature space. We don't include here the full description of the K-Means algorithm as it is out of scope of our topic. The drawbacks of this method are that we need to specify the number of clusters beforehand and also K-Means clustering does not take into account spatial information of the image.

D. SLIC Segmentation

Another method widely utilized for images segmentation is based on the superpixels. A superpixel is a polygonal part of a digital image, larger than a normal pixel, that is rendered with uniform color and brightness. Simple Linear Iterative Clustering groups pixels in the combined five-dimensional color and image plane space to efficiently generate compact superpixels [8].

E. Split and Merge Segmentation Algorithm

Splitting and merging attempts to divide an image into uniform regions. The basic representational structure is pyra-

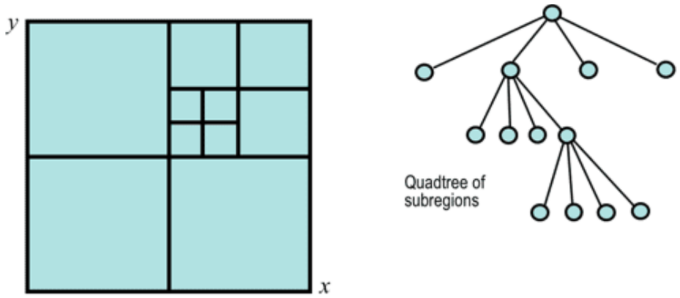


Fig. 8. Split and Merge Algorithm

midal, i.e. a square region of size M by M at one level of a pyramid has 4 sub-regions of size $M/2$ by $M/2$ below it in the pyramid. The algorithm starts from the initial assumption that the entire image is a single region, then computes the homogeneity criterion for the considered region to see if it is TRUE. If FALSE, then the square region is split into the four smaller regions [9]. For a gray-scale image a region is said to be statistically homogeneous if the standard deviation of the intensity less than some threshold value, where the standard deviation is given by:

$$\sigma = \frac{1}{N-1}\sum_{i=0}^{N}(x_j - < x >)^2 \tag{5}$$

This process is then repeated on each of the sub-regions until no further splitting is necessary. These small square regions are then merged if they are similar to give larger irregular regions, Fig. 8. The problem (at least from a programming point of view) is that any two regions may be merged if adjacent and if the larger region satisfies the homogeneity criteria, but regions which are adjacent in image space may have different parents or be at different levels (i.e. different in size) in the pyramidal structure. The process terminates when no further merges are possible.

III. EXPERIMENTS

For the experimental part we took a 200x200 pixels Sentinel-2 image of the region in Minnesota, USA. We have performed segmentation of this image using different approaches described in Section II. We tried to vary the parameters of the algorithms to get different number of the segmented regions. The results of our experiments are discussed in Section IV. To perform numerical comparison we used the following evaluation methods.

A. Evaluation Methods for Image Segmentation [2]

Unsupervised evaluation methods evaluate segmentation results by using a quality evaluation function. The key advantage of unsupervised evaluation is that it enables an objective comparison of different segmentation methods without making a comparison with a manually-segmented reference image, which is often referred to as ground truth. We use the evaluation functions E and Q in an unsupervised evaluation method because these require no user-defined parameters and are independent of the content and type of image. Before describing the evaluation metrics, some notations and definitions are given. Let I be the segmented image with height I_h and width I_w. Let S_I be the area of the full image and S_j be the area of region j. Evaluation function E consists of region entropy (Hr) as the measure of intra-region uniformity, and layout entropy (Hl) is the entropy indicating which pixels belong to which regions. The E function, which combines these two measures, is defined as:

$$E = H_l(I) + H_r(I) \tag{6}$$

where

$$H_l(I) = \sum_{j=1}^{N}\frac{S_j}{S_I}\log\frac{S_j}{S_I} \tag{7}$$

$$H_r(I) = \sum_{j=1}^{N}\frac{S_j}{S_I}H(R_j) \tag{8}$$

$$H(R_j) = \sum_{j=1}^{N}\frac{L_j(m)}{S_j}\log\frac{L_j(m)}{S_j} \tag{9}$$

Where N is the total number of regions, V_j is the set of all possible values associated with the intensity in the region j, and $L_j(m)$ denotes the number of pixels in region j that have a value of m for intensity in the panchromatic image.

Another segmentation accuracy estimation method utilized in this work was proposed by Liu and Yang [7]. They empirically defined following evaluation function:

$$F(I) = \frac{1}{1000MN}\sqrt{R}\sum_{j=1}^{R}\frac{e_j^2}{\sqrt{S_j}} \tag{10}$$

where: I is the segmented image, NxM, size of the image, R, the number of regions in the segmented image, S_j, the area of pixels of the j-th region, and e_j the color error of region j. The color error in RGB space is calculated as the sum of the Euclidean distances between color components of pixels of region and components of average color, which is an attribute of this region in the segmented image.

The evaluation function Q proposed by Borsotti et al. (1998), which measures mean squared spectral error of the segments, is defined as:

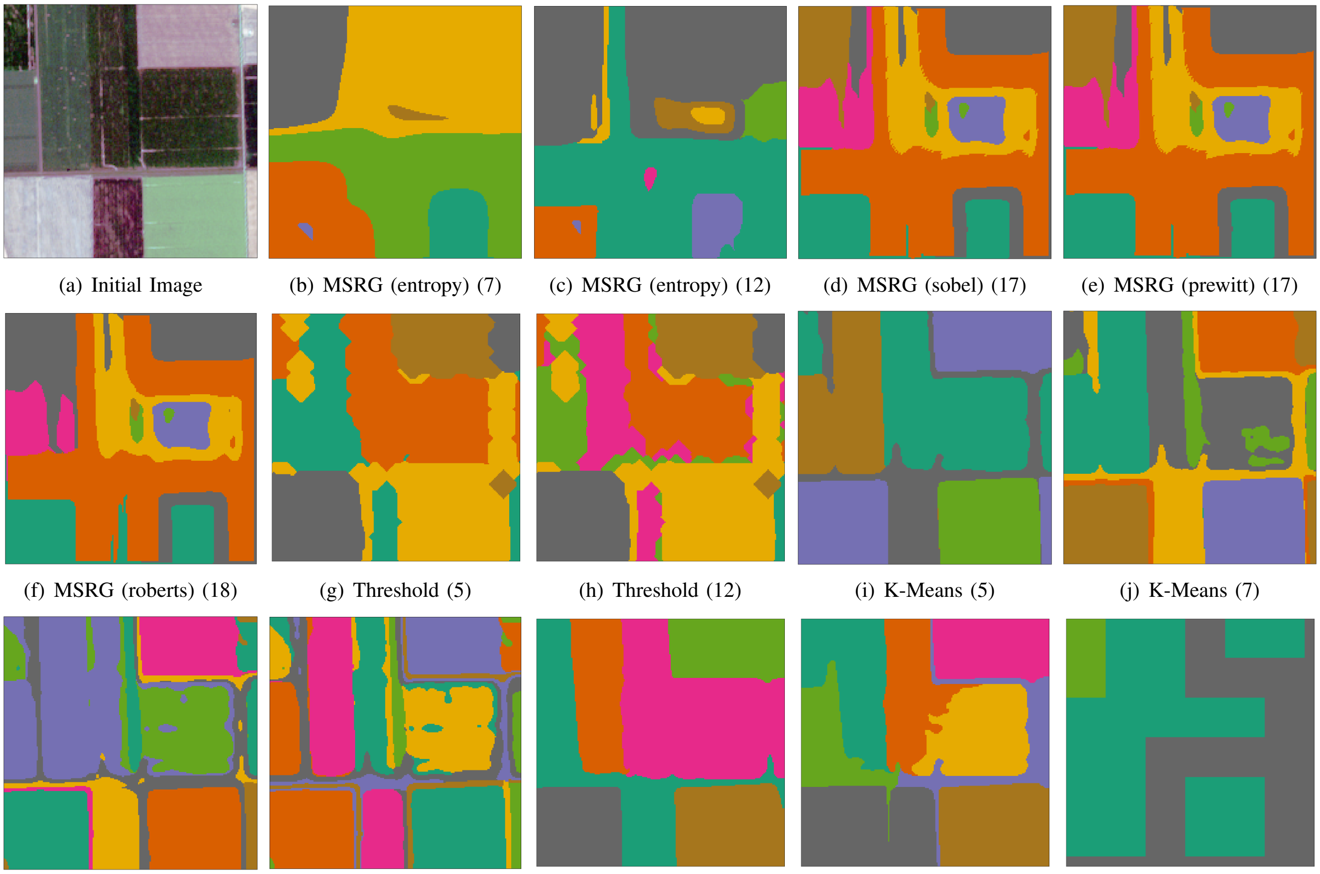
$$Q(I) = \frac{1}{1000MN}\sqrt{R}\sum_{j=1}^{R}(\frac{e_j^2}{1+\log S_j} + (\frac{N(S_j)}{S_j})^2) \tag{11}$$

$N(S_j)$ represents the number of regions that have an area equal to S_j.

Generally, the smaller the values of E, F, and Q, the better the segmentation results for the image.

IV. RESULTS

We present the results of different segmentation approaches for different number of regions on Fig. 9. There are the numbers of regions in brackets for each of the images. The numerical results according to the evaluation methods presented in Section III are shown in Table I. The # column in this table corresponds to the number of regions for the



(a) Initial Image (b) MSRG (entropy) (7) (c) MSRG (entropy) (12) (d) MSRG (sobel) (17) (e) MSRG (prewitt) (17)

(f) MSRG (roberts) (18) (g) Threshold (5) (h) Threshold (12) (i) K-Means (5) (j) K-Means (7)

(k) K-Means (12) (l) K-Means (17) (m) SLIC (6) (n) SLIC (9) (o) Split Merge (3)

Fig. 9. Visual Comparison of the Results

TABLE I

SEGMENTATION RESULTS

Method	#	H_l	H_r	E	F	Q
MSRG (entropy)	7	1.49	4.90	6.39	0.00029	0.002
MSRG (entropy)	12	1.75	4.92	6.68	0.00127	0.010
MSRG (sobel)	17	2.03	4.73	6.76	0.00289	0.017
MSRG (prewitt)	17	2.03	4.73	6.76	0.00289	0.017
MSRG (roberts)	18	1.97	4.74	6.71	0.00337	0.021
Threshold (500 pix)	5	1.56	**0.32**	**1.88**	0.00119	0.010
Threshold (300 pix)	12	2.01	2.05	4.06	0.03024	0.225
Threshold (200 pix)	22	2.39	2.63	5.02	0.17883	1.103
K-Means	5	**1.21**	3.48	4.69	0.00028	0.002
K-Means	7	1.59	3.84	5.43	0.00030	0.002
K-Means	12	2.18	4.21	6.39	0.00062	0.004
K-Means	17	2.33	3.13	6.06	0.00180	0.009
SLIC	6	1.38	2.84	4.22	**0.00007**	**0.001**
SLIC	9	1.88	3.11	4.99	0.00050	0.003
SLIC	14	1.85	3.30	5.16	0.00051	0.003

segmented image. Also, for each of the MSRG methods there are edge-detection operators in brackets and for each of the Threshold methods there are the minimum numbers of pixel for the regions in brackets.

Visually, the results deffer by the algorithms. For example, MSRG produces sometimes oversmoothed results, especially when the number of regions is small. Threshold algorithm produce some artifacts on the boundaries of the segments,it also requeres individual adjustment of parameters, like smoothing degree, optimal number of morphological operations, for every new image. There is no the best single algorithm for this task. However, numerical comparison indicates that the better performance is obtained when segmenting the image into five regions, but the ground truth is that the initial image has more than five segments obviously. Also, the optimal solutions according to the metrics are the Threshold and K-Means, but these two methods can mark the areas in different parts of the image as the same segment, which is not naturally what we want. For the inverse reason, it is difficult to obtain good metrics values for the MSRG algorithm, as it generates segments as inseparable areas. The SLIC algorithm produces the segmentation with very small F and Q values for number of regions equals 6, but the result seems undersegmented.

It should be noticed that metrics F and Q penalize more segmentation with many regions, but metric E also takes into account the regions entropies H_l, which are desired to be small, and thus prevents undersegmentated results.

CONTRIBUTION

Ruslan Agishev: implementation of the Threshold Image Segmentation Technique, application of SLIC Segmentation, Split and Merge Segmentation Algorithm, implementation of the evaluation metrics Q and F.

Vasilii Mosin: implementation of the MSRG Image Segmentation Algorithm, implementation of the K-Means Cluster-Based Segmentation, implementation of the evaluation metrics H_l, H_r and E.

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